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CNN PERFORMANCE IMPROVEMENT USING WAVELET PACKET TRANSFORM FOR SCA PREDICTION

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ABSTRACT

Sudden cardiac arrest (SCA) is a medical emergency that poses the risk of death to the patient. For prevention, a robust system is intensively on ongoing research to predict whether a person may predict sudden cardiac arrest in the future, long before the incident. The current system development method is learning from the patient's ECG recordings. A combination method between the Wavelet Packet Transform and the Convolutional Neural Network classification model was proposed to obtain hidden patterns from the patient's ECG recordings. The SCA dataset was obtained from the MIT-BIH SCA Holter DB with 2 ECG machines and the Normal Dataset from the MIT-BIH Normal Sinus Rhyme. With cross-validation evaluation with k-fold=10, by comparing one segment 1 minute from 30 minutes before onset, Convolutional Neural Network (CNN) performed with an accuracy of 95.89%, precision of 96.75%, recall 95.83%, and F1-Score 95.75%, with two-level Meyer Wavelet Packet Transformation.

Keywords: *Sudden Cardiac Arrest, Electrocardiogram, Wavelet Packet Transform, Convolutional Neural Network*

1. INTRODUCTION

Sudden Cardiac Arrest (or SCA) contribute to 20% of cardiovascular-related death in an industrial country. The cause of Sudden Cardiac Arrest is the presence of arrhythmic beats called Bradyarrhythmia [1][2]. One of the examples of the beats is Ventricular Fibrillation (VF) which contributes to 60%-85% of the SCA [3], mostly happening to the younger generation and heavily work-out personnel such as athletes and military officers [4]. To prevent SCA attacks, monitoring the suspected at least 1-hour before the incident [5] to predict SCA occurrence by monitoring ECG activity is necessary to increase patient survivability, which is crucial for patients who live in a crowded area without sufficient emergency facilities.

As the SCA prediction method based on Electrocardiography (ECG) monitoring is joint research by several researchers, the main challenge is the limited data specified for the SCA case [6]. Several successful methods to detect SCA vary from using morphological features [7], implementing wavelet feature engineering [8], [9], using HRV feature and its derivation [10]–[12], and employing sophisticated methods such as ensembled classifier with HRV feature [13]. On the other hand, with the advent of the Convolutional Neural Network (CNN), the researchers also tried to exploit CNN to ECG-related methods from the SCA case, which gave promising results [14]–[17]. At the same time, the research attempts to achieve the suggested time fails [18]. However, when several researchers struggled with revealing the underlying pattern inside a normal-like SCA signal pattern with the healthy signal one, other research related to CNN employed the wavelet method to enhance feature engineering by the model and increase the accuracy[19], [20].
This research aims to contribute to academic research related to SCA or healthcare by replacing the traditional machine learning methods from the past, such as SVM, KNN, and Random Forest, with the CNN model optimised by wavelet preprocessing. We offer a new approach to detect SCA longer than existed offset time. At the same time, we also provide an alternative method to simplify the feature extraction process to distinguish features for both

SCA and normal healthy conditions. We investigate the possibility of implementing Wavelet Packet Transform decomposition by feeding the decomposed signal into own-built CNN architecture and comparing it with the performance using a raw signal only since the minimal feature extraction method is commonly practised when using CNN classifier. From there. We also want to prove previous claims where a CNN performance could be enhanced using wavelet-based transformation for different cases.

This paper explanation is written into several sections: we review and summarise the previous research in Section 2, description about our proposed method in Section 3, the evaluation result of the technique and the comprehensive explanation in Section 4, the conclusion of our experiment, and the process in Section 5.

2. RELATED RESEARCH

Several existing kinds of literature which observed SCA has a different approach to detecting SCA for a specific time frame before the VF onset is shown. For example, Ebrahimzadeh et al. [11] investigate the possibility of linear and nonlinear features extracted from the Heart Rate Variant (HRV) to discriminate the SCA-like signal from the healthy signal, where the SCA-like signal taken from a 1-minute segment from 4 to 1 minute before VF onset showed. However, when evaluated using MLP 4 minutes before VF, the feature gave a poor performance, with 83.96% accuracy. On the other side, Amezquita et al. [21] investigate the possibility of Wavelet Packet Transform (WPT) to create a Homogeneity Index from the transformation result as their feature. This approach has 95.8% accuracy for a 1-minute segment taken from 20 minutes before VF onset shown. Another Wavelet-related feature was investigated by Fujita et al. [9]. They developed the Sudden Cardiac Arrest Index (SCDI) method to create features from Discrete Wavelet Transform (DWT), which gives 98.6% accuracy at 4 minutes before VF onset is shown. Another SCDI investigation was also held by Lai et al. [12] for 30 minutes before VF onset was established, which gave 99.49% accuracy when evaluated with Random Forest. However, this result was obtained using a supported external dataset, the AHA Database, which is unavailable publicly alongside MIT-BIH datasets, which consist of the Sudden Cardiac Holter Dataset (SCDH) [22] and Normal Sinus Rhymes (NSR) [23], which commonly used for SCD case. Shi et al. [13] employ Ensemble Empirical Mode Decomposition (EEMD)-based entropy features extracted from HRV to detect 14 minutes before VF is shown, with 96.1% accuracy. Instead of a 1-minute segment, they used two-minute segments of ECG record to extract it. HRV.

In contrast, Muruguppan et al. [7] used morphological features taken from HRV and employed a Support Vector Machine (SVM) classifier for 5 minutes before VF was shown, giving 100% accuracy. We could note some critical issues and challenges from the SCA-related research. First, we note that most traditional machine learning methods for classifying SCA and Normal signals have limited performance since they can only perform for a shorter time before the incident. We also noted insufficient data to fulfil a reliable experiment for the SCA, which resulted in one of the researchers using support datasets to increase the number of the data.

Since Convolutional Neural Network (CNN) is new for cardiovascular cases, most research about ECG analysis using CNN is more focused on arrhythmia cases. The most common approach to represent an ECG signal for CNN feature is using 1-Dimension data (1 x length of feature size). This approach was used by Avanzato et al. [16] to investigate 4000 heartbeat chunks with an accuracy of 98.33% with a 1-dimension, and both Acharya et al. [15] and Baloglu et al. [14] with the exact case which investigated a Myocardial infraction and same dataset. While the Baloglu method could perform 99.00% with 651 input elements, Acharya performed 93.5% and 95.22% accuracy using 550 input elements. We need to note that Acharya applied their method for both clean and noisy signals.

Instead of using a 1-Dimension signal, Zhai et al. [17] employ the 2-Dimension feature by coupling two heartbeats from two ECG channels, which gives an accuracy of 99.1% for Ventricular Ectopic 97.3% for Supraventricular Ectopic beat. We could note that most CNN me used unprocessed or minimum pre-processing ECG signal in their paper, which contrasts with most SCA research we reviewed that used HRV as the feature.

Since some result of the CNN-related test is promising with the smaller dataset for the SCA case, we investigate the method to strengthen the CNN classifier using a preprocessed form. However, CNN alone can create its feature to classify an object. For this case, the DWT decomposition was explored by Fujieda et al. and Williams et al. when both proposed methods for the image-based case. Williams et al. [19] experimented with one-level and two-level wavelet decomposition and fed the decomposed feature into blocks of parallel CNN. With the

MNIST dataset, their proposed method could perform with an accuracy of 99.67% with four pieces of the decomposed image, compared with 99.11% of the pure CNN method, while with the CIFAR-10 dataset, they performed 85.67% compared with 77.53% of pure CNN.

On the other hand, Fujieda et al. [20] used channel-wise concatenation in their CNN architecture, in contrast with the parallel-processing architecture of Williams. Experimented with Recurrent Image Annotation (RIA) method compete with existing VGG-16 architecture. They claimed better overall results than VGG-16 using the IAPR-TC-12 and Microsoft COCO dataset, with the overall F1-Score for the first dataset being 37.54 and 55.16 (pure VGG-16 F1 scores 34.40 and 55.47). We could note that the wavelet could optimise the CNN performance from both results.

From all related works of literature, for the SCA-related method, the wavelet based-feature is the most commonly used in previous research, especially the WPT method, which gives a longer prediction time before the VF onset with standard datasets. In contrast, CNN offers promising results in ECG-related areas. However, since we learn that the standard-issue bout between SCA and Normal signals before the VF onset is harder to differentiate, we found that wavelet preprocessing before CNN classification can improve the classification for a longer time.

3. PROPOSED METHOD

Our method consisted of several stages, as shown in Figure 1. First, signal preprocessing is implemented, and then the preprocessed signal is segmented. We collected WPT-decomposed features and raw signals from segmentation to evaluate our method using CNN. We observe 30, 20, 10, 5, 4, and 1 minute before SCA occurrence for evaluation using three kinds of wavelet function: Daubechies 4 and 6 (coded as db4 and db6) and Meyer (coded as "dmey").

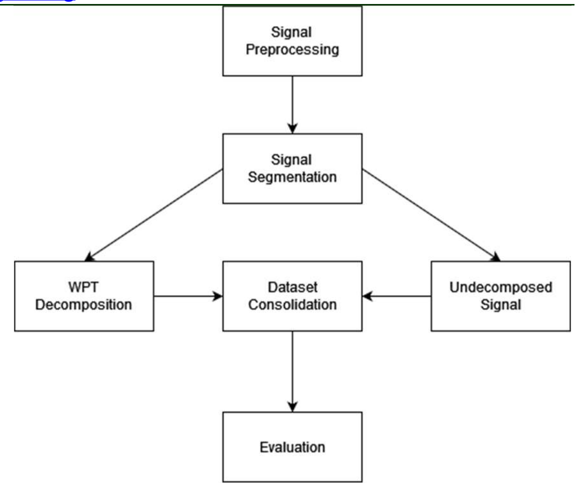

FIGURE 1. Experiment Sequential

3.1. Data and Signal Processing

To follow previous research, we used MIT-BIH SCDH and NSR Datasets. SCDH datasets consist of 23 ECG records from 17-89 years old patients, varying from 7 hours to longer than one day. Since only 20 out of 23 records have VF onset marked when the VF occurs and the point when SCA happens (no.40,42 and 49 not included), these 20 records are used in observation. On the other hand, NSR consists of 18 healthy regular heartbeat records at a long duration (the duration for each record was not mentioned).

Since SCDH and NSR records have different frequency samples (250Hz for SCDH and 128Hz for NSR), both SCDH and NSR datasets are sampled to 128Hz and only use the first lead from each record since the first and second lead comes from the same person. The following process removes noise using a third-order Butterworth Filter with a band between 0.5Hz – 30Hz and 60Hz band-pass to eliminate electrical interference.

For each SCDH record, other researchers commonly employ both channels (ECG 0 and 1, respectively). Each 1-minute segment from 30 minutes is taken from VF onset backwards, resulting in 30 different parts. For each NSR record, both channels were used for our observation, and each 1 minute from the overall segment was taken randomly since the NSR dataset did not have an underlying health issue.

3.2. Wavelet Feature

4-level decomposition with Daubechies 4,6 and Meyer wavelet function is deployed for each segmented signal. Since WPT resulted in both detail and approximation nodes, we experimented with concatenate approximation and detail nodes to form input to our model. We employ a 4-times WPT decomposition, where each result of the decomposition is chained together. A signal chunk was decomposed with each level's chosen mother wavelet function, resulting in the Approximation dan Detail compound, coded as A and D.

Since the WPT process decomposed both approximation and detail compound for each subsequent level, each combination resulted in an approximation and detail compound from the previous decomposed compound. For example, in the second level, an approximation compound from 1st becomes an approximation and detail compound from the approximation chunk in the 2nd level, which is coded as AA and AD.

Since most CNN methods reviewed for ECG signal classification employed 1 Dimension input, a straightforward approach is used to meet this condition. Instead of processing each level individually as implemented by William [19] or Fujieda[20], we concatenated each approximation and detail compound by chaining each combination illustrated in Figure 2.

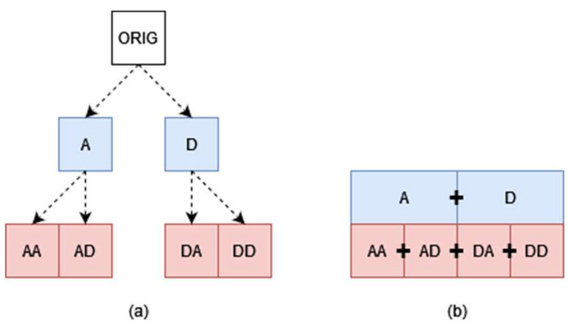

FIGURE 2. WPT decomposition schema (a) following with feature construction from decomposed (b)

3.3. Classification

We designed our CNN architecture to feed a 1-dimension feature described in Figure 3, inspired by one CNN-based classifier for the ECG case from Xi et al. l[24]. We use two layers of 1-D Convolution with 128 x 5 dimensions and Relu activation function. Then a Max pooling layer was added with a size 1x3 dimension to eliminate weak features, followed by two 1-D Convolution with 128x5 and 256x5 behind the Max Pooling layer. After that, A-Max Pooling with 1 x 3 kernel is added, followed by a Dropout with neuron turn-off probability to 0.5 at the end of the last Convolution 1D. Then the network is closed with a fully connected layer with dense sigmoid and two classes (SCD and Normal). Adamoptimiserr deployed for the model with 10-batch chosen**.** As we stated in Section 3.2, we employed 1-D CNN architecture to follow the specification of previous research in ECG while, on the other hand simplifying the CNN architecture.

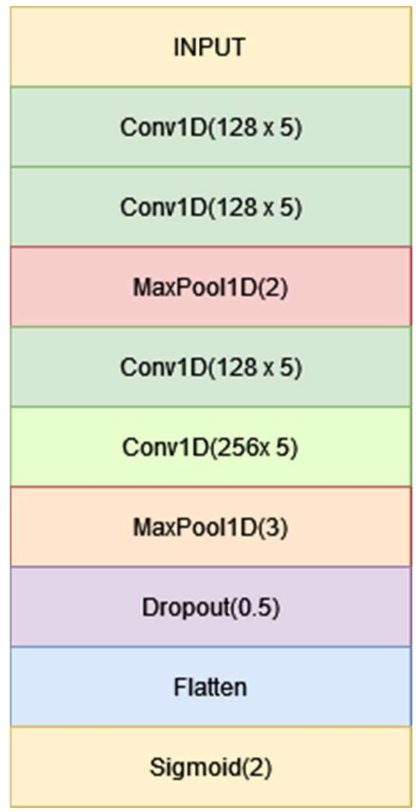

FIGURE 3. CNN Architecture

3.4. Evaluation

For evaluation, we use the cross-validation method 10-fold. Each minute in observation is evaluated using a 9:1 training-test proportion for each fold, employed with other research when considering CNN [25]. We evaluated our method from 30, 20,10,5,4, and 1 minute before VF onset occurrence for each test to compare our proposed result with previous research. We use standard performance metrics in the last research accuracy, precision, recall, and F1-score, where the score is calculated from the average for all folds. As we mention in the introduction section that there is a possibility to increase the model's performance by performing a wavelet preprocessing procedure at the face of the CNN classifier, we also compare our model with raw signal without wavelet preprocessing.

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We explain our experiment result in two sections: First, we describe the frequency and chunks of the feature. Second, we reported our findings from each method's CNN classification result. We focused our result on the accuracy, precision, recall, and F1-Score instead of timing performance since most of the previous research in SCA focused on these metrics.

4. EXPERIMENT RESULT

4.1. Feature Presentation

Since chunk chaining of feature gives the same feature lengths as raw one, the frequency band of each level represents each band of a chunk. This frequency could help CNN to reveal underlying abnormal heart activity [26] while, on the other hand, it helps CNN to create sufficient knowledge to increase classification performance [19]. Each decomposition level could lead to lower frequency and shorter chunks, which meet the condition of the Nyquist Theorem [27]. However, since the CNN architecture used for each minute is the same, the frequency level and mother wavelet choice influence the final result of each method.

Since we used a one-dimensional feature, as mentioned in Section 3.2, we represent our feature to concatenate both approximation and detail chunks from wavelet decomposition. Table 1 shows each level's feature representation, where the approximation is coded as 'a and details are coded as 'd'.

We also analyse the chunk description resulting from the wavelet decomposition to ensure that the wavelet library we used is correct and usable to decompose the signal. Table 2 verifies that each level, chunk number, and decomposition feature's length has been correctly implemented. Since we used Wavelet Packet Transform, both approx and details coefficients are equally decomposed, unlike conventional DWT. As a result, each decompositions chunks are twice the previous level, and the length should be half of the coefficient length from the upper level, since in the wavelet concept, for each decomposition, the coefficient length will be reduced by half from the previous level. Since the size of the chunk decreased by a multiplier of two, the frequency, according to the Nyquist theorem also reduced by the multiplier of two, where the highest level will be reduced to 64Hz. On a deeper level, the frequency was reduced to 8Hz.

TABLE 1. Feature Decomposition Concatenation

Level	Feature representation
1	['a', 'd']
2	['aa', 'ad', 'da', 'dd']
3	['aaa', 'aad', 'ada', 'add', 'daa', 'dad', 'dda', 'ddd']
4	['aaaa', 'aaad', 'aada', 'aadd', 'adaa', 'adad', 'adda', 'addd', 'daaa', 'daad', 'dada', 'dadd', 'ddaa', 'ddad', 'ddda', 'dddd']

TABLE 2. Feature Description

Level	Chunk(s)	Length	Chunk Frequency
1	2	3840	64Hz
2	4	1920	32Hz
3	8	960	16Hz
4	16	480	8Hz

4.2. CNN Parameters

The Proposed CNN model used in our research was developed with Tensorflow using parameters mentioned in Section 3.3 at the top of the CUDA backend provided for Nvidia GTX 1050ti. We also simplified our model using a smaller feature size in our convolution layer for memory efficiency.

From our model, as we mentioned before, the input size for each wavelet decomposition output and raw signal are identical, to thus parameters used for the CNN. The 982.373 trainable parameters used by our CNN architecture were in the last layer total of 653.413 flatten features for classified Normal or SCA signal chunks. The detailed information of each layer can be seen in Table 3.

TABLE 3. feature Description

Layer	Input	Output	Parameter
Input	7.680	7.680 x 1	-
Conv	7.680	7.676 x 128	768
Conv	7.676 x 128	7.672 x 128	82.048
MaxPool	7.672 x128	3.836 x 128	-
Conv	3.836 x 128	3832 x 128	82.048
Conv1D	3.832 x 128	3828 x 256	164.096
MaxPool	3.828x 256	1.276 x 256	-
DropOut	1.276x256	1.276 x 256	-
Flatten	1.276 x 256	326.656 x 1	-
Sigmoid Dense	326.656	2	653.413
TOTAL			982.373

4.3. Performance Result

The result for each minute varies. The frequency and mother wavelet methods could achieve the best outcome for 30 minutes by dmey mother wavelet with an Accuracy of 95.89% and an F1 score of 95.75%, as informed in Table 1. There is an insignificant difference when the accuracy score is compared with the F1 score. Since our dataset is slightly imbalanced (there is 2 data difference between the SCA class and the non-SCA class), we can verify that our proposed method enhances the result compared with the basic undecomposed feature (accuracy 87.67% and F1 score 82.57%). This performance improvement proves the assumption of wavelet possibilities to improve CNN performance.

Besides the result, the wavelet decomposition level tied with the wavelet function influenced the outcome. This informed us that each wavelet decomposition has its optimum level of decomposition to give such performance, as mentioned in Tables 4 to 9. According to Nyquist Theorem, for each wavelet decomposition, the frequency of the feature is lowered by half of its original frequency. From this theory, since the original signal for NSR and SCDH is sampled equally at 128Hz for 30 minutes of detection, Meyer (dmey) wavelet had the optimum decomposition level at 2nd decomposition or 32Hz since there are more critical features that could be gathered from the signal at this frequency.

However, the method performed well in the comprehensive test when we evaluated it 20 minutes before. Although dmey shown works optimally for 30 minutes before VF onset as shown in Table 3, at this observation, db6 performs better as shown in Table 4 with 97.5% of accuracy and 97.5% of F1 score, improved from the accuracy of 81.67% and F1 score of 75.04% for raw unprocessed signal. At this observation, db6 has a similar decomposition level compared with dmey at 30 minutes before VF onset and the frequency.

From our observation, the method performs poorly for 4 minutes before the VF occurrence. Even the technique can increase the accuracy from 89% to 95%, as mentioned in Table 7; however, the result is lower than 30 and 20 minutes in Tables 4 and 5. The Daubechies 6 in this level can increase the accuracy using two decomposition levels.

5. DISCUSSION

The result analysis has several discussion points according to the outcome. First, our wavelet-based method performance has a lower deviation than non-wavelet optimisation. For example, we calculate the standard deviation for all accuracy of the best performance obtained by our wavelet-based method and compare the result with the deviation of the raw signal. Based on the calculation, the wavelet optimised has a standard deviation of 1.02, outperforming the non-wavelet with 3.30. From Figure 4, the performance for the non-wavelet feature tends to decrease for each observation minute before onset, shown in contrast with the wavelet-based method, which is more stable.

To investigate the performance deviation based on the wavelet method, we do the standard deviation based on the best accuracy performance on each observation minute. From this calculation, although Meyer obtained the best accuracy for our goal at 30 minutes before the onset, Daubechies 6 showed more stable performance for each observation time with a standard deviation of 0.95 compared with Meyer with 1.4 and Daubechies 4 with 1.06. Thus, Meyer also has similar behaviour with the basic feature that tends to decrease even when observed 1 minute before onset. In contrast, Daubechies 6 and 4 tend to increase while the observation minute reduces, as shown in Figure 5.

Second, we can confirm the possibility of using WPT to increase CNN performance with important notices. From 30 minutes to 1 minute before SCA onset, both mother wavelet choice and decomposition level significantly influence the result. This is related to the concept of wavelet. For each decomposition process, the signal's frequency decreased by half from the original, emphasising such frequency band's feature. The optimum frequency band for better performance depends on the wavelet function used to decompose the signal, resulting in different results for different optimum decomposition levels for different wavelets.

However, we admitted that our proposed method performed poorly for one of the evaluation scopes (4 minutes), where our approach performed poorly compared with other observed minutes. In contrast, the process performed better for a longer observation time, which also covered our research time target.

The main challenge behind the longer misdetection happened when detection was performed for a more extended time before the incident. Patients with SCA's ECG signal showed a similar pattern to the regular heartbeat patient

[28], which was visually identical to a healthy patient. However, using the WPT method by decomposing each signal, underlying information which discriminated SCA conditions from normal healthy signals in patients with SCA signals could be revealed [29].

When we compared our result with other research in Table 10, we could claim that CNN combination with WPT enhancement could surpass both time and accuracy for previous studies. Comparing with multiple feature method as employed by previous studies, we can achieve the higher result with simplified the feature extraction method without further feature processing, compared with wavelet-related approach studied in [9],[21],[30] . At the same time, we also proof the method given by [19], [20] has similar impact to improve performance of the CNN classification method.

However, we also admit that in several observation minutes, our method cannot exceed the performance achieved by method from previous research, especially with the similar time scope of 30-minutes before SCA [12]. However, we need to note that the mentioned research employs an additional dataset, which differs from most SCA detection studies. Nevertheless, compared with similar methods such as DWT for 5 and 1 minutes before VF onset [9], or even identical WPT to observe 20 minutes before VF onset happens [21], our optimisation method has proven to slightly increase the accuracy performance.

Table 4. Performance On 30 Minutes Before Vf Occurrence

f(x)	dec level	Accuracy	P	R	F1
(dmey)	2	95.89	96.75	95.83	95.75
(db6)	3	95.00	96.33	95.00	94.79
(db4)	1	95.00	95.50	95.00	94.96
Raw		87.67	87.83	82.50	82.57

Table 5. Performance On 20 Minutes Before Vf Occurrence

F(X)	Dec Level	Accuracy	P	R	F1
(dmey)	3	94.82	96.00	94.58	94.63
(db6)	2	97.50	97.50	97.50	97.50
(db4)	3	94.46	95.08	94.17	94.26
Raw		81.67	78.92	77.92	75.04

Table 6. Performance On 10 Minutes Before Vf Occurrence

f(x)	dec level	Accuracy	P	R	F1
(dmey)	3	94.46	94.83	94.58	94.38
(db6)	3	96.07	97.00	95.83	95.90
(db4)	1	96.07	96.25	96.25	96.07
Raw		85.00	76.67	80.83	77.28

Table 7. Performance On 5 Minutes Before Vf Occurrence

f(x)	dec level	Accuracy	P	R	F1
(dmey)	1	94.64	96.00	95.00	94.54
(db6)	2	95.00	96.00	95.00	94.92
(db4)	4	96.25	96.50	96.25	96.23
Raw		81.67	79.08	77.50	75.05

Table 8. Performance On 4 Minutes Before Vf Occurrence

f(x)	dec level	Accuracy	P	R	F1
(dmey)	3	92.14	93.08	92.08	92.00
(db6)	2	95.00	96.33	95.00	94.79
(db4)	3	94.82	95.75	95.00	94.76
Raw		89.00	88.58	85.00	84.63

Table 9. Performance On 1 Minute Before Vf Occurrence

f(x)	dec level	Accuracy	P	R	F1
(dmey)	3	94.46	95.50	94.58	94.32
(db6)	3	96.25	97.00	96.25	96.19
(db4)	2	97.50	98.00	97.50	97.46
Raw		84.33	85.92	82.08	81.96

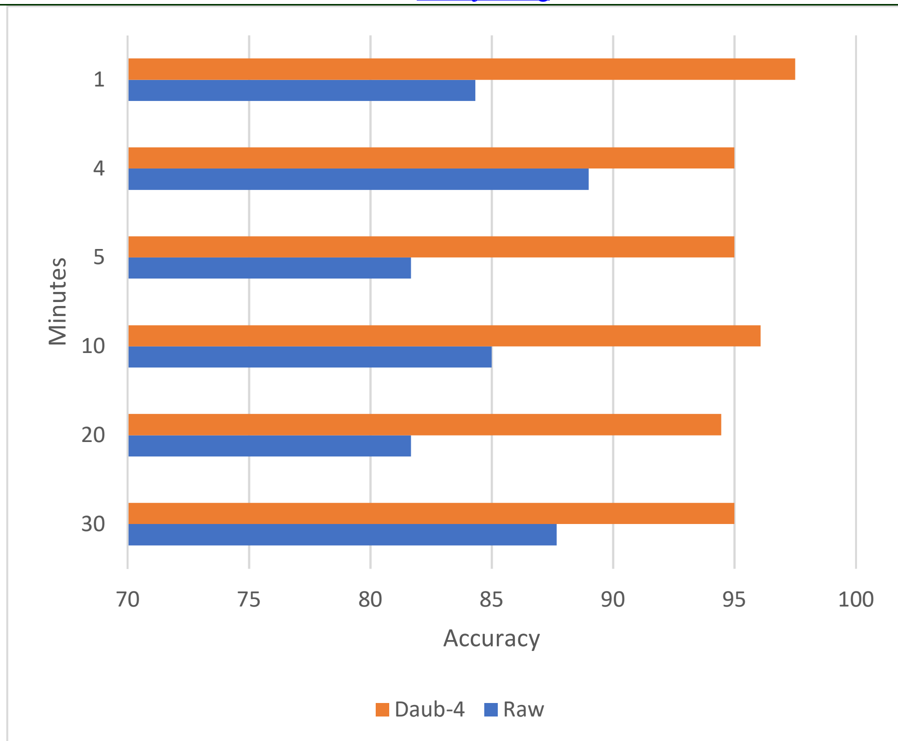

Figure 4. Comparison Between Wavelet-Optimized (Overall Best Accuracy) Vs Raw

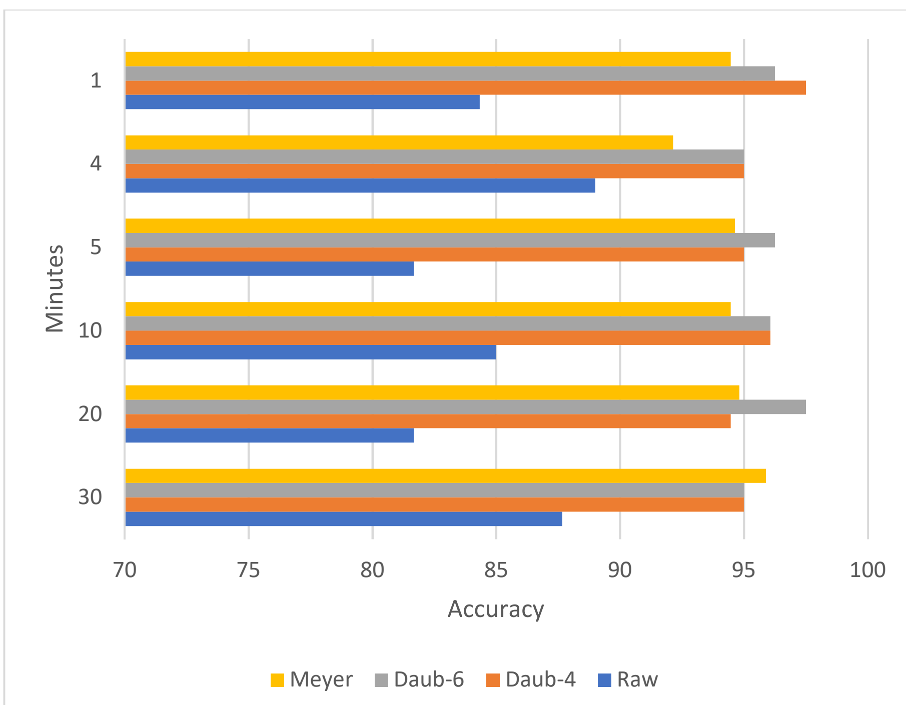

Figure 5. Comparison Between Each Wavelet Function (Best Accuracy) Vs Raw

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Table 10. Comparison With Similar Research

Previous Research	Method	Time before onset	Accuracy
[21]	Wavelet Packet Transform + E-PNN	20	95.80%
[13]	HRV + E-PNN	14	96.1%
[10]	Poincare Plot + Recurrence + KNN	5	94.10%
[9]	DWT + SCD Index + SVM	5	92.11%
	DWT + SCD Index + KNN	1	92.11%
[30]	SVM-RBF	5	94.7%
[11]	MLP	5	83.96%
		1	99.73%
[7]	HRV Morphology + SVM	5	100%
[12]	SVM + HRV + SCDI (*)	30	99.49%
Proposed	WPT + CNN	30	95.89%
		20	97.50%
		10	96.07%
		5	96.25%
		4	95%
		1	97.50%

6. CONCLUSION AND FURTHER WORKS

In this research, we have achieved our hypotheses according to possibilities of wavelet Wavelet Packet Transformation method for CNN performance enhancement in the case of Sudden Cardiac Arrest prediction. As per our observation, our proposed method performs better at the 2nd level, with the frequency for each lead being 32Hz for 30 minutes before SCA occurs. Our proposed CNN model can also fulfil the research time target to classify 30 minutes before SCA, with 95.89% accuracy, 96.75% precision, 95.83% recall, and 95.75% F1-Score. With this performance result, our method outperformed previous research in [21] with the WPT approach on both before onset and accuracy (30 minutes compared with 20 minutes before) with similar data for valid comparison. However, this result is still unsatisfiable since the real-life expectancy of 1 hour before an incident is still a gold standard and commonly used in most medical facilities worldwide, and studies to develop robust yet proven method to reach the gold-standard requirement is suggested.

Even with the high performance shown, with limited data, the amount of data used for both the training and evaluation processes is minimal, thus raising another concern about whether this approach is feasible to be used in the actual case. From that, a new proposal to create sufficient data is proposed by the researcher [6] to raise the validity and feasibility of the result.

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In future works, we will explore possible methods to optimise CNN architecture with the Wavelet method since most of the related research with wavelet performs well compared with other methods. We also need to explore feasible CNN models that can learn wavelets better for a longer time (1 hour or more) due to medical necessity, while expanding ECG data sources for SCA cases are parallelly taken.

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